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LOCAL BINARY PATTERNS BASED DETECTION OF RUST DISEASE OF LENTILS (*Lens culinaris*) USING k-NN CLASSIFICATION SYSTEM

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ABSTRACT

This research paper reported the role of k-Nearest Neighbor (k-NN) classifier for detection and classification of rust disease of Lens culinaris at microscopic level, which is a very initial stage of disease i.e. haustorium stage found in bean crops. Detection of the rust disease present on the surface of leaves was diagnosed at an early stage before going to spore stage, responsible for spreading of rust disease to the other plants. The average filter and Local Binary Patterns (LBP) were used for preprocessing and feature extraction, respectively, for detection of rust disease. For testing propose k-Nearest Neighbor (k-NN) classifier was used and the average classification accuracy found 91% of the test samples using k-NN. The work initiates automatic recognition of rust disease found in bean crops at a very early stage.

KEYWORDS: Rust Disease, Local Binary Patterns, k-Nearest Neighbor Classifier & Lens culinaris

Original Article

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INTRODUCTION

In North India, Lentil rust is a serious fungal disease caused by the pathogen Uromyces viciae- fabae. It occurs in the form of yellowish brown, small pustules surrounded by halo zone, present mainly on the leaves, as shown in Figure 1b, as the disease develops, spores of rust spread to the other parts of plants, other plants and even to the other fields. This disease can also occur on the stems and pods and the rust pustules are similar but larger in size than the leaves. Winter season is favorable for occurrence of diseases when temperature is increased up to 20-25 °C at a growing stage of plants (Taylor *et al*, 2007). The presence of humidity in the environment is a very important factor for fungal as well as bacterial infections of commercial crops (Swan *et al*, 2000; sang *et al*, 1992). Most of the plant pathologist observed rust disease by naked eyes for identifications and used fungicides to control disease. In developing countries, mainly in India, experts use fungicides for controlling fungal disease in the fields which cause adverse effect on the human life. So, it is an emergent need to identify rust disease automatically and diagnose rust disease as early as possible before spreading to other plants as well fields as shown in Figure 1a, where disease occur but can't observe by naked eyes. In this work, these leaves were used for image data using a microscope.

Now days, computer added detection/CAD is becoming popular after rising interest of computer scientist towards agriculture. Image processing and pattern recognition techniques for automated identification of rust disease of crops have been studied. An automatic and accurate method was developed by Varghese Pt *et al* (2016) to detect and discriminate rust disease of Wheat. Previously in our lab, Sabrol *et al*, (2013) used image processing methods to identify rust disease of Wheat crop. Local Binary Pattern for feature extraction was reported by many

scientists for disease detection, such as fungal disease of vegetable crops (Jagadeesh *et al*, 2014), Ocular disease recognition (Preeti *et al,* 2014) and Diabetic Macular Edema (DME) detection (Al-falluji, 2016). Ojala *et al* (2002) reported the Local Binary Pattern (LBP) operator for feature extraction. This operator is very efficient and basically used to describe the texture and shape of a digital image.

In this present work, we have proposed and experimentally validated the significance of using k-NN classifier for the automatic detection and classification of rust diseases in Lentils.

Figure 1: Leaves of Lentil Plant *(Lens culinaris)* with Rust Disease: a) Leaves with Hyphae and Haustoria at Early Stage; b) Leaves with Spores and Pustules and Yellow Colonies

PROPOSED METHODOLOGY

In this proposed work, we have applied image processing and pattern recognition techniques for detection of rust disease at initial level. The proposed methodology that applied in this work is shown in Figure 2, in which we followed the microscopic image acquisition, preprocessing, image smoothing, segmentation, feature extraction using LBP and sample images was tested by k-NN classifier.

Image Set

The leaves of Lentil plant (Lens culinaris) affected by rust disease are considered in the present work. The symptoms of rust disease found on leaves considered for recognition and classification. The leaves samples were collected from Hill Agricultural Research and Extension Centre Dhaulakuan, Himachal Pardesh, India.

Image Acquisition Method

Sample leaves were collected, washed and sterilized for preparation of microscopic image data according to Sangeetha *et al*, (2012) with some modifications. 1% (w/v) solution of aniline blue dye prepared in distilled water for staining of hyphea and historium of rust disease. After staining, leaves samples were observed under Light microscope (Leica DFC425C). Images acquired by the microscope are shown in Figure 4a.

PREPROCESSING AND SEGMENTATION

Image pre-processing was used to improve the quality of image by image smoothing using average filtering, reduce blurring and enhancing image that increases the chances for the proper identification of infected parts of the leaf. A two dimensional filter by type averaging was used to filter the image by averaging the pixel values within the window of the filter. Figure 3a and 3b shows a 3x3 mask for weighted average and how the mask is convolved to filter the image.

Figure 3c depicts a 3x3 average filter in the frequency domain. Thresholding (Otsu, 1979) is the simplest method of image segmentation and used to create binary images from a grayscale image (Figure 3b). In binary image, the value of “0” and “1” is represented by background pixel and an object pixel, respectively (Shapiro *et al,* 2001).

Feature Extraction

After smoothing and enhancing the quality of the input image, features will extract from that image. For the feature extraction purpose, in the proposed work, Local Binary Patterns operator was used for sampling image. Conversion of sample image in the set of features is known as feature extraction (Ojala *et al,* 2002). Feature extraction is basic the operator used for differentiating class of the objects and also improve quantitative as well as qualitative information of the features of interest. The original LBP operator labels the pixels of an image with decimal numbers 0 (no color saturation), and 1 (full saturation), which encode the local structure around each pixel as patterns (Tiger *et al,* 2013).

According to Ojala *et al* (2002), the notation (P, R) is used for pixel neighborhoods and defined as an ordered set of binary comparisons of pixel intensities between the central and its surrounding pixels. The equation (1) of expression is given below

$$\mathrm{LBP}_{P,R}\,(x_i\,, y_i) = \sum_{n=0}^{7} S(p_n - p_i)2^n \tag{1}$$

Where pi corresponds to the central pixel (xi, yi), pn corresponds to the 8 surrounding pixels, and function S(c) is defined as

$$S(c) = \begin{cases} 1 \text{ if } c \geq 0 \\ 0 \text{ if } c \leq 0 \end{cases} \tag{2}$$

One basic limitation of LBP operating is that less than 8 neighborhoods cannot extract the features with large scale structures. So, we are using 8 neighborhood pixels, i.e. 2^8 = 256 patterns. Histogram of 256 patterns can be used for feature extractions.

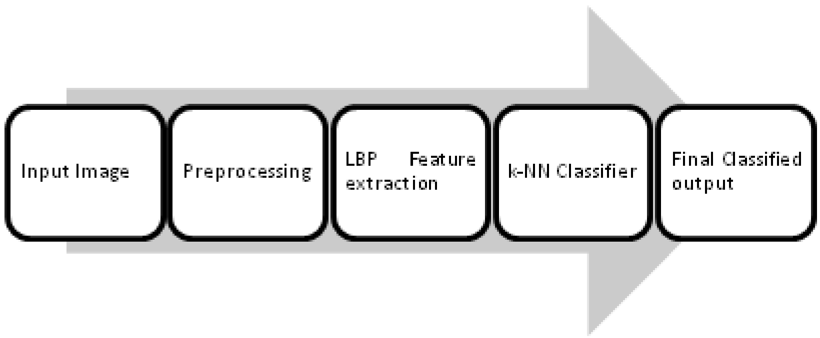

Figure 2: Design Steps of Proposed Methodology

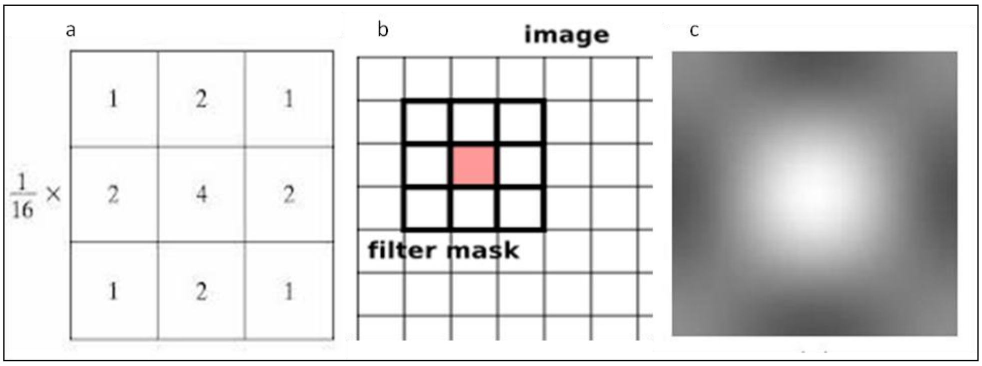

Figure 3(a): Average Filter Mask; b) Image Filtering with Mask; c) Frequency Domain representation of 3x3 Average Filters

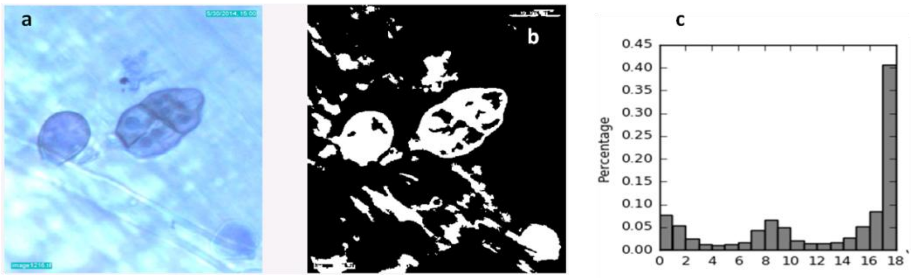

Figure 4: Preprocessing of Microscopic Image of Stained Leaves with Aniline Blue Dye; a) Haustorium of Rust Disease of Lentil; b) Preprocessing of Image; c) Feature Extraction Using Local Binary Patterns (LBP)

RESULTS AND DISCUSSIONS

This work considers 700 images of 5-6 days old seedling leaves as shown in Figure 1a. We used the young leaves before the appearance of spores on the surface of leaves. At this stage only microscopic analysis can confirm the rust disease by history and hype growth which is very initial stage and help in controlling of disease. Haustoria and hyphal growth of leaves observed after staining with dye and sample images were divided in two two groups. One group was used for training and other used for testing and carried out with LBP features and k-NN classifier.

In this work, we used k-NN to classify the rust disease at initial stage as it is the simplest method of classifying patterns based on the class of closest pattern i.e. nearest neighbor. Suppose k = n, then n objects were assigned its nearest neighbors. The “K” value was represented by (Jagadeesh *et al,* 2014)

$$K=\sqrt{\text{number of feature sets}}$$

We used k-NN classifier for testing data to make timely short which is need of real time applications. Proposed disease stage classifier could easily classify the stages of rust disease based on feature texture. The layout of the process of detection and classification is represented by an algorithm.

It was observed that the maximum identification and classification accuracy of 91% were founded by testing of 100 sample images of rust disease. So the detection of early stage of rust disease would be very helpful for agriculturist as well as farmers.

Algorithm

Start

```
clear all
close all
load('KNNClassifier.mat');
n=100;
test_out=[];
for i=1:n
I = imread(strcat('Testing (',num2str(i),').tif'));
green = I (:, :, 2);
 levels = multithresh (green, 3);
 level = double (levels(1))/255;
 BW = im2bw (green,level);
 BW = 1-BW;
 I2 = I (:,:,2).*unit8(BW);
 H=lbp(I2);
        knn_out = predict(knn_classifier,H);
         test_out(i,:) = [knn_out];
end
for i=1:6
   accuracy(i) = (n-length(find(test_out(:,i)~=1)))*100/n;
end
```

CONCLUSIONS

- In this paper, LBP and k-NN classifiers were applied for identification and classification of rust disease Symptoms in early stage on the leaves of Lentil crop. Though k-NN is very simple classifier, but the limit of the k - NN classifier is that it can be generated only with the training samples and it does not use any additional data. Due to this limitation algorithm depend on the training set excessively and recalculation of analysis needs, even in small change in training settings. So we can overcome this limit by applying another classifier such as Support vector machines, Back Propagation Neural Network and others.
- This work can be extended to classify visual symptoms affected by rust disease found in beans crops and other commercial crops.

- Detection of disease at an early stage will be promising step for a plant pathologist to control disease completely by applying low as well as effective dose of fungicides before spreading of the disease to other plants and field to field.
- These methods can also be used to identify various other diseases of bean crops caused by viruses and bacteria

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